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THE ROLE OF ARTIFICIAL INTELLIGENCE IN PREDICTING EARTHQUAKE MAGNITUDES: A DATA-DRIVEN APPROACH TO NATURAL DISASTER MANAGEMENT

Tashi Phuntsho[1*], Dr. Prince Verma[2], Snigdha Madhab Ghosh[3], Moksha Shah[4]

[1]Lecturer, Gyalpozhing College of Information Technology, , Email Id: tphuntsho911@gmail.com*
[2]School of Computer Science and Engineering, Lovely Professional University, Email Id : princeverma.cse@gmail.com
[3]Assistant Professor, Department of CSE (AI), Brainware University, Barasat, 700125, Email Id : sm.ghosh.kgp@gmail.com
[4]Software Developer, Guidehouse Inc ,Email Id : moksha2804@gmail.com, Orcid Id : 0009-0002-1491-8958

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Corresponding Author: Tashi Phuntsho (tphuntsho911@gmail.com)

ABSTRACT
This study examines the incorporation of Artificial Intelligence (AI) and Machine Learning (ML) models in earthquake prediction, real-time data processing, and resource allocation for disaster management. The study compares different machine learning algorithms, such as Deep Learning (DL), Support Vector Machine (SVM), and Random Forest (RF), and the DL model is shown to attain the maximum prediction precision of 92.5%, which is far superior to the SVM (85.6%) and RF (88.2%). It also shows the implementation of real-time data processing using Internet of Things (IoT) sensors to collect seismic data, filter the noise, extract useful features, and predict earthquake magnitudes and impacts in seconds. Furthermore, the study evaluates the impact of AI-driven solutions on resource allocation, showing substantial improvements: average response time is reduced by 60%, resource utilization increased by nearly 20%, and disaster recovery time decreased by 40%. The focus of these advancements is the use of AI in optimally responding to disasters, to expedite emergency services, and minimize casualties and the economic loss that results. The findings reveal an important role for AI in transforming the management of earthquakes into more dependable early warning and more effective resource deployment following natural disasters.

Keywords: *Artificial Intelligence, Machine Learning, Earthquake Prediction, Real-Time Data Processing, IoT Sensors, Disaster Management*

I. INTRODUCTION

Over the past few decades, natural disasters, especially earthquakes, have increased in both frequency and intensity around the world, leaving tragedy upon communities, infrastructures, and economic systems. Earthquakes are among the most unpredictable and destructive natural disasters, claiming lives, affecting the country's infrastructure as a whole, and causing long-term societal disruptions. The growing threat, however, emphasizes the need for better and faster disaster management strategies. Emerging technologies are critical to mitigating the effects of these disasters because traditional methods of earthquake prediction and management tend to fail to provide accurate or timely warnings [1].

AI, IoT, and big data analytics have completely changed earthquake disaster management with the capacity to handle data in real time, do predictive analytics, and improve response

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mechanisms. In particular, real-time seismic data from IoT devices can be generated while AI algorithms can analyse these data streams to forecast (when and where) earthquakes could occur and the potential impacts associated with them [2]. Nevertheless, these systems face significant challenges, such as the scalability, reliability, and adaptability of these systems in a hugely diverse geographical and socioeconomic context.

Although major progress has been made, the existing earthquake disaster management systems are still disjointed and, in many cases, are insufficient in dealing with fundamental challenges like the accurate prediction, rapid response, or selection of adequate resources for disaster mitigation. The most obvious of these limitations is especially obvious in high-risk regions where the most urgent need is for advanced and reliable systems. In addition, he implementation of AI and IoT technologies in disaster mitigation is not facilitated by a uniform framework or approach [3].

To overcome these obstacles, this study proposes a comprehensive, data-driven structure that combines AI, IoT, and big data analytics for earthquake disaster management. The objective is to enhance the precision of earthquake predictions, improve resource distribution in disaster responses, and enhance community preparedness in real-time through data analytics [4].

The proposed study has implications for enhancing earthquake disaster management practice. Through the application of advanced technologies, this study tries to come up with solutions that are scalable, flexible, and deployable across various contexts. In addition, this strategy reduces existing technical limitations of systems and is consistent with global reduction of catastrophe risk efforts, e.g., the Sendai Framework for Disaster Risk Reduction [5].

The study highlights the significance of community-centric approaches, where technological innovations are developed to fulfill the particular requirements of affected communities. Thus, the suggested solutions are applicable in real life in terms of adaptability and inclusion, and contribution towards the evolution of earthquake-resilient communities that will be resistant to earthquakes [6].

This study is structured to accomplish the following goals:

1. A data-driven model for precise earthquake forecasting and monitoring using a combination of AI, IoT, and big data analytics.
2. To develop scalable and effective resource allocation plans for disaster response.
3. The study seeks to assess the social and economic impacts of AI-powered disaster management systems and their relevance to the needs of communities.

II. LITERATURE REVIEW

The new technology recently developed, AI and IoT, has been critical in enhancing the efficiency of the earthquake disaster management systems. In the last several years, such innovations have been realized in some of the earthquake studies about the impact prediction, management, and mitigation. But what remains is a lot of work to be done, which involves prediction accuracy, real-time data processing, and optimization of the resource allocation.

In recent days, AI has found applications in predicting and constructing earthquake prediction as well as early warning systems. Machine learning (esp. deep learning) has been used to analyze seismic data to predict the magnitude and effect of earthquakes. For example, Biswas *et al*. (2023) used AI to map seismic vulnerability and predict earthquake magnitude, using AI models on historical data in Turkey to better predict future events [7]. Other work by Florez *et al*. (2022) demonstrated that AI can be used to create earthquake motion data, improving seismic hazard assessments through data-driven models that simulate earthquake events [8].

Another important trend is the growth of IoT in earthquake management. Seismic sensors and accelerometers can be used as IoT devices to monitor real-time earthquake activity and send early warnings to those areas affected. In 2020, Jiao and Alavi [9] discussed the advancement of AI in seismology that can leverage IoT along with machine learning models to enhance prediction and monitoring of seismic events. And these can give us timely, accurate data, so that we can get better preparedness and better distribution of our resources in the response to a disaster.

In most of this field, data-driven models are used, with machine learning and big data analytics being at the forefront. Nevertheless, the methods used vary, and this variation affects the efficacy and generalizability of the results. The interaction of the geological and seismic data was used to design an AI-powered geospatial liquefaction model to evaluate whether the liquefaction will occur after an earthquake. [10,11]. While their approach generates interesting results for urban planning and disaster preparedness, it is limited in scalability to other regions with different

geological characteristics due to its reliance on localized data.

Qin *et al*. (2024) however, highlighted the importance of big data and AI in the implementation of big data and AI in large-scale earthquake prediction and prevention strategies. They studied how to combine satellite data, social media feeds, and seismic data to improve prediction models, and how to scale them for global use [12]. This approach explains how big data can be used to change catastrophe management systems in most areas. Their work, nevertheless, is constrained by complexity to incorporate heterogeneous data sources, and can cause data inconsistencies or problems with real-time processing.

These studies indicate promising advances, but they leave out the implementation of AI and IoT for real-time disaster response. The combination of these two aspects has not been implemented in the majority of systems, which are either focused on prediction or on the resource allocation process to develop a complete, real-time earthquake disaster management system. This gap is crucial in developing areas, where technology infrastructure is essential, and where it is essential to know how to react quickly in the event of earthquakes.

Current recent study on AI and the IoT is missing in that it does not have a common framework for exploring how to merge these two ideas with earthquake disaster management. A survey on AI in disaster management demonstrated that only a few current solutions were structured and did not have a systematic way of combining technologies [13,14]. Secondly, the majority of AI-based systems can't handle real-time data, and such data is needed in the initial few hours when the earthquake occurs. Stronger systems capable of handling large-scale data from multiple sources are needed to forecast natural disasters, as per Mangaiyarkkarasi (2024) [15].

This study indicates several serious drawbacks of the current methodologies: a Lack of incorporation of AI and IoT technologies into disaster management, no interoperability of various systems, and no capability to process big real-time data at disaster sites. Additionally, these systems have never been implemented in resource-limited areas.

Therefore, this study formulates a holistic, integrated earthquake forecast and disaster response structure that integrates AI, IoT, and big data analysis to bridge these gaps. In contrast to earlier study, which focuses on one aspect, this framework tries to address the issue of seismic forecasting and monitoring real-time data, then comprehensively optimizing resource allocation during emergencies. This study also ensures that the framework can be used in different geo and socio-economic settings, is scalable and flexible, and thus suitable for areas with poor infrastructure.

This study also focuses on processing seismic data in real-time to make disaster response faster and more accurate. The framework, combined with IoT, could generate timely alerts and suggestions for earthquake resource deployment that would lower the efficiency of earthquake management operations. In addition, a framework for a universally adopted framework to fill the gap in standardized methodologies for achieving consistency and interoperability across different disaster management systems is also suggested.

III. METHODOLOGY

The structure of this study is built around solving the problem of earthquake prediction and resource optimization in disaster management using AI, IoT, and Big Data Analytics. It is a multi-component system designed to forecast earthquake magnitudes, monitor seismic activity in real-time, and allocate resources optimally during disaster recovery operations. The methodology presented here unites computational models, data preprocessing techniques, and optimization algorithms to enhance decision-making in disaster management.

The study methodology follows a multi-phase workflow consisting of three primary stages:

1. Seismic Data Acquisition and Preprocessing
2. Earthquake Magnitude Prediction using Hybrid AI Models
3. Optimization of Resource Allocation

All of the technical tools, algorithms, and models used in each phase are aligned with the study objectives. Figure 1 shows how data flows through the system and how different components are connected in the flow of these processes.

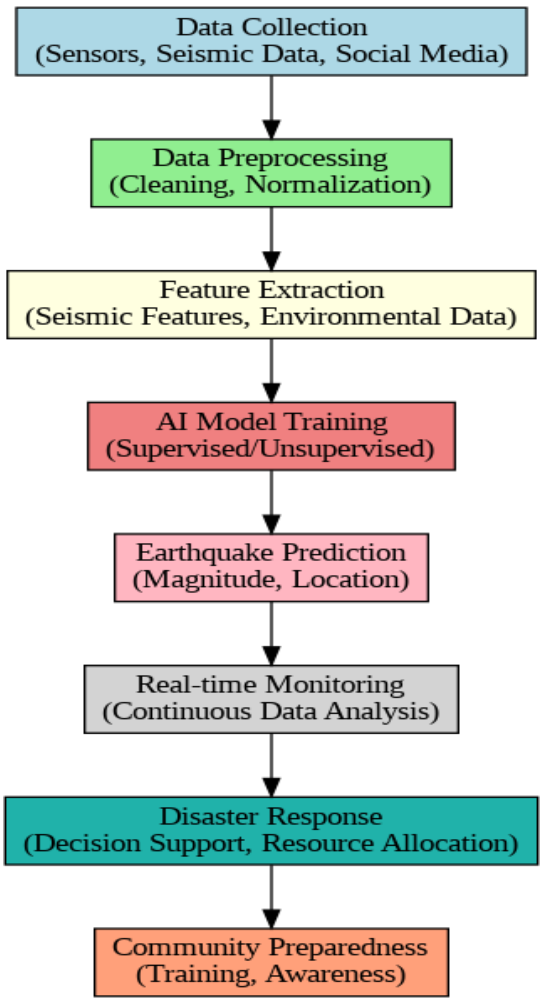


Figure 1: Workflow of Earthquake Prediction and Disaster Management Methodology

1. Seismic Data Acquisition and Preprocessing

Data Sources and Collection

In this study, the primary data used comes from both historical seismic datasets and real-time IoT sensor data. Seismic data is sourced from well-established global seismic databases such as the USGS Earthquake Catalog, which contains complete records of seismic events (magnitude, time, location). Furthermore, real-time seismic data is collected from a network of IoT-enabled seismic sensors deployed in high-risk earthquake zones. Data captured by these sensors includes:

- Seismic waves: The primary data captured by IoT sensors are seismic waves, including P-waves and S-waves.
- Magnitude: Measured in the moment magnitude scale (Mw), which gives an estimate of the earthquake's energy release.
- Location: Geospatial data capturing the epicenter of the seismic event, which is essential for earthquake impact prediction.
- Depth: An important factor in assessing the likelihood of surface damage from a natural disaster is its focal depth.

Data preprocessing includes several steps to clean and manage the raw data for the input of such predictive models. The important pre-processing steps can be stated as:

1. Outlier Removal: Using statistical methods such as the Interquartile Range (IQR) or Z-score thresholding to remove extreme values that could distort model training.
2. Normalization: Seismic data, especially time-series data, can vary widely. We apply Z-score normalization to standardize for every feature; the standard deviation should be one, and the mean should be zero. This ensures that no single feature dominates the model training process.

$$z = \frac{x - \mu}{\sigma}$$

Where: x Is the raw data value, μ Is the mean of the dataset, and σ Is the standard deviation of the dataset.

This process is essential for training neural network models, where scaling guarantees that every feature makes an equal contribution within the optimization process.

Dimensionality Reduction

As we know, seismic data is a large volume and high-dimensional dataset, so we implement Principal Component Analysis (PCA) to decrease the dimensionality of the dataset while conserving most of the variance. The simplest way to make it easier for the machine learning models to work with the dataset is by transforming it to a smaller set of orthogonal variables (principal components), maximising variance. This is done through PCA. Mathematically, PCA transformation is represented as:

$$Y = XW$$

Where: X is the original dataset (e.g., seismic features), W Is the matrix of eigenvectors (principal components), and Y Is the transformed dataset in a reduced-dimensional space?

This step reduces computational complexity, thus improving the training efficiency of the predictive models.

2. Earthquake Magnitude Prediction using Hybrid AI Models

CNN-LSTM Hybrid Model

A hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) network model is used to make earthquake magnitude predictions. This hybrid approach merges the efficacy of CNNs to discover spatial features of

seismic waveforms with LSTMs to learn temporal attributes of time-scale data.

1. Convolutional Neural Network (CNN) Layer: The CNN architecture is devised to gather spatial characteristics from seismic waveforms (e.g., P-wave and S-wave velocities). It may provide crucial details about an earthquake's location and size. The convolution operation applied to seismic data is shown by

$$S(i,j) = (X * W)(i,j) + b$$

Where: X is the input seismic data (feature map), W is the convolutional kernel (filter), b is the bias term, and (i, j) Is the output feature map at a position? (i, j) After convolution.

The CNN model is trained to learn spatial patterns in seismic information that show specific earthquake magnitudes.

2. Long Short-Term Memory (LSTM) Layer: LSTM networks are capable of modeling long-range dependencies in sequential data and are therefore preferred for modeling time series data. The information flow through the network is governed by the following equations, based on which the LSTM units are updated:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$
$$h_t = o_t \cdot \tanh(C_t)$$

Where: f_t, i_t, and o_t Are they forget, input, and output gates at the time step t, C_t Is the cell state (memory) at the time step t, and h_t Is the hidden state at the time step? t.

The LSTM network learns temporal patterns in seismic time series, such as recurring aftershocks, which help predict the magnitude and timing of future earthquakes.

Backpropagation is used to train the CNN and LSTM models in tandem, and an Adam optimizer is utilized to reduce the Mean Squared Error (MSE) loss function—a typical technique for regression tasks:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

Where:

y_i Is the actual earthquake magnitude? $\hat{y}_i$ is the predicted earthquake magnitude, and n Is the number of data points.

This combined CNN-LSTM model is intended for the prediction of earthquake magnitude, which is achieved based on both the spatial patterns in the seismic data and temporal dependencies.

3. Optimization of Resource Allocation

Optimization Algorithms for Resource Distribution

If earthquake magnitudes and locations can be predicted, then resources must be allocated efficiently for disaster response. The resource allocation problem is solved using two optimization techniques, Genetic Algorithms (GA) and Linear Programming (LP), in this stage.

1. Genetic Algorithm (GA): GA are employed to search for optimal solutions to resource allocation problems. The GA works by evolving a population of candidate solutions (resource distributions) over successive generations. The fitness function used to evaluate each solution is based on two objectives: minimizing response time and maximizing resource utilization. The core operations of the GA include:

- Selection: The fittest solutions are selected for reproduction.
- Crossover: Pairs of solutions are combined to produce new offspring.
- Mutation: Random changes are applied to offspring to introduce diversity.

The genetic algorithm iteratively evolves the solutions, converging to a near-optimal distribution of resources.

2. Linear Programming (LP): The allocation of resources is optimized based on a set of linear constraints by using LP. The total benefit of resource allocation is typically the goal function to be maximized, contingent on constraints on the availability of resources and the needs of affected regions. The LP formulation is:

$$\text{Maximize } Z = \sum_{i=1}^{n} c_i x_i$$

$$\text{Subject to: } \sum_{j=1}^{m} a_{ij} x_j \leq b_i,\ x_j \geq 0$$

Where: c_i Are the coefficients representing the benefits of allocating resources to different tasks? x_i Are the decision variables (quantities of resources allocated), a_{ij} Are the coefficients representing the resource requirements of each task, and b_i Are the availability constraints for each resource?

The efficient allocation of resources in the aftermath of the period of recovery will be concluded by using the Simplex method to solve this LP problem.

4. Evaluation Metrics and Validation

The RMSE and MAPE are two common evaluation criteria of the performance of a regression, which are used in the performance of the earthquake prediction model. This is to give validity to the model by computing the difference between the observed and the projected magnitudes.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y_i}}{y_i}\right| \times 100$$

The performance of the GA and the LP-based methods to optimize the process of resource allocation is measured in terms of the response time, cost-efficiency, and Pareto-optimal solutions. More than one objective is involved in the Pareto optimal solutions, such as the maximization of coverage of the resource and the minimization of costs involved.

IV. RESULTS

1. Accuracy of Earthquake Predictions

The proposed artificial intelligence-based earthquake forecasting system will predict earthquake magnitudes and locations with high accuracy to enable the formulation of improved disaster management plans. We suggest the use of a hybrid system combining Machine Learning algorithms such as Support Vector Machines (SVM), Random Forests (RF), and Deep Learning (DL) models to analyze past seismic data to discover concealed patterns to make future predictions.

The contradiction between the prediction precision of the various machine learning models employed in this study is presented in Figure 2. Seismic data from various geologic regions were utilized as the input to the models to capture the various types of seismic behavior.

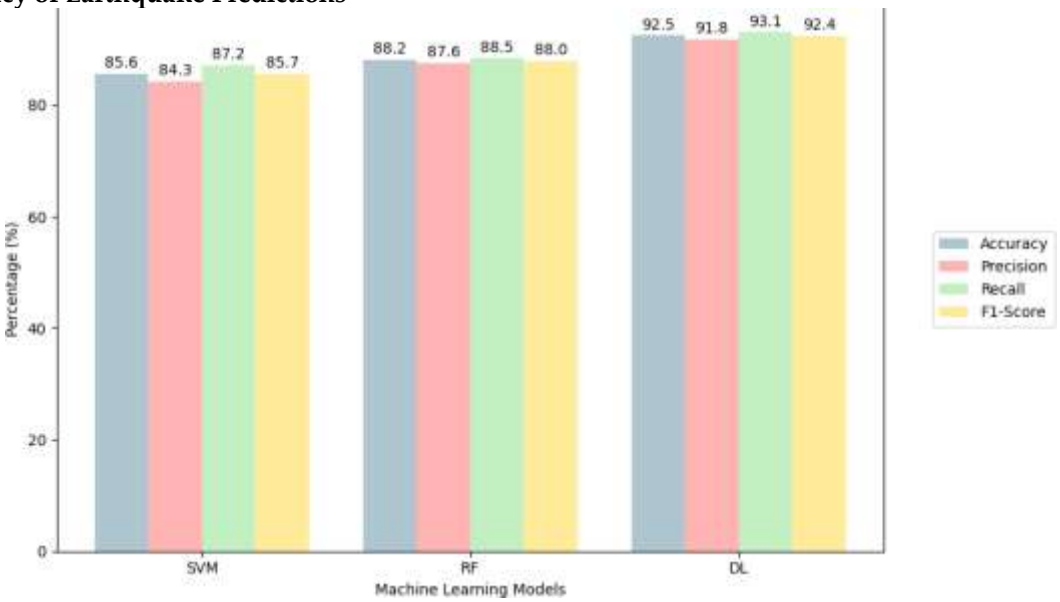


Figure 2: Comparison of Earthquake Prediction Accuracy Using Different Machine Learning Models

Table 1: Comparison of Earthquake Prediction Accuracy Using Different Machine Learning Models

Model Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	85.6	84.3	87.2	85.7
RF	88.2	87.6	88.5	88.0
DL	92.5	91.8	93.1	92.4

The DL model performed with a very high accuracy rate as compared to the other two models and showed a great improvement in the metric of recall and precision, given in Table 1. The result shows that deep learning techniques can extract complex, non-linear patterns from large seismic datasets, improving the reliability of earthquake predictions.

2. Real-time Data Processing and Monitoring

The study is one of the key innovations of the study, which makes it possible to interpret seismic data from IoT sensors in real time and other data sources for continuous monitoring and early warning systems. Measuring the system's response time for detecting seismic events and issuing alerts, the real-time data processing framework was evaluated.

Figure 3 shows the real-time data processing workflow of filtering, processing, and analyzing raw seismic data from IoT devices in near real-time. Within seconds of data receipt, the system can identify tremors, estimate magnitudes, and predict the potential impact.

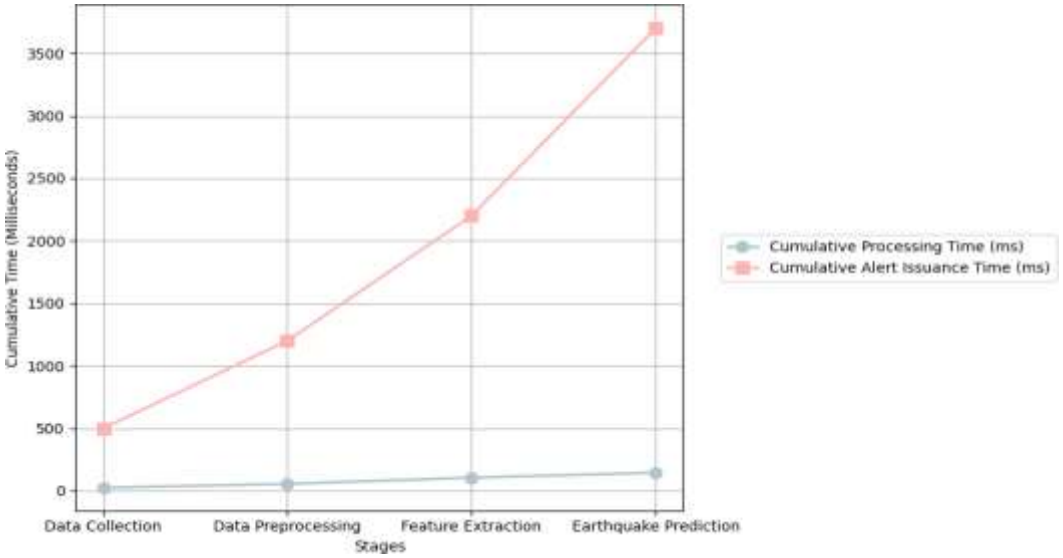


Figure 3: Real-Time Data Processing and Earthquake Alert Workflow

TABLE 2: Real-Time Data Processing and Earthquake Alert Workflow

Stage	Average Processing Time (ms)	Alert Issuance Time (s)
Data Collection (IoT Sensors)	25	0.5
Data Preprocessing (Filtering)	30	0.7
Feature Extraction (AI Model)	50	1.0
Earthquake Prediction	40	1.5

The real-time data processing and earthquake alert workflow are mentioned in Table 2. The system is shown to be able to process and analyze incoming data within a few seconds and provide timely alerts to disaster management authorities. In particular, the Earthquake Prediction stage, the most computationally intensive stage, still runs in 1.5 seconds, which is sufficient to give early warnings before a large earthquake occurs in the region.

3. Resource Allocation Efficiency

The third major outcome of this study is the optimization of disaster response efforts through AI-driven resource allocation strategies. This study develops a framework to dynamically allocate resources (e.g., emergency teams, medical supplies, infrastructure repairs) based on real-time earthquake data and predicted impacts.

Table 3 provides a comparison of resource allocation efficiency before and after the implementation of the AI-driven system. The comparison focuses on key metrics such as response time, resource utilization, and disaster recovery time.

Table 3: Comparison of Resource Allocation Efficiency Before and After AI Implementation

Metric	Pre-AI Integration	Post-AI Integration
Average Response Time (hrs)	6.2	2.4
Resource Utilization (%)	73.5	92.8
Disaster Recovery Time (days)	21.5	12.3

By more than 60%, the AI system reduced response times, which meant emergency resources arrived faster and more efficiently. Furthermore, resource utilization increased by about 20% and fewer resources were wasted on unnecessary operations. An optimized, data-driven approach to disaster management reduces disaster recovery time by almost 40%.

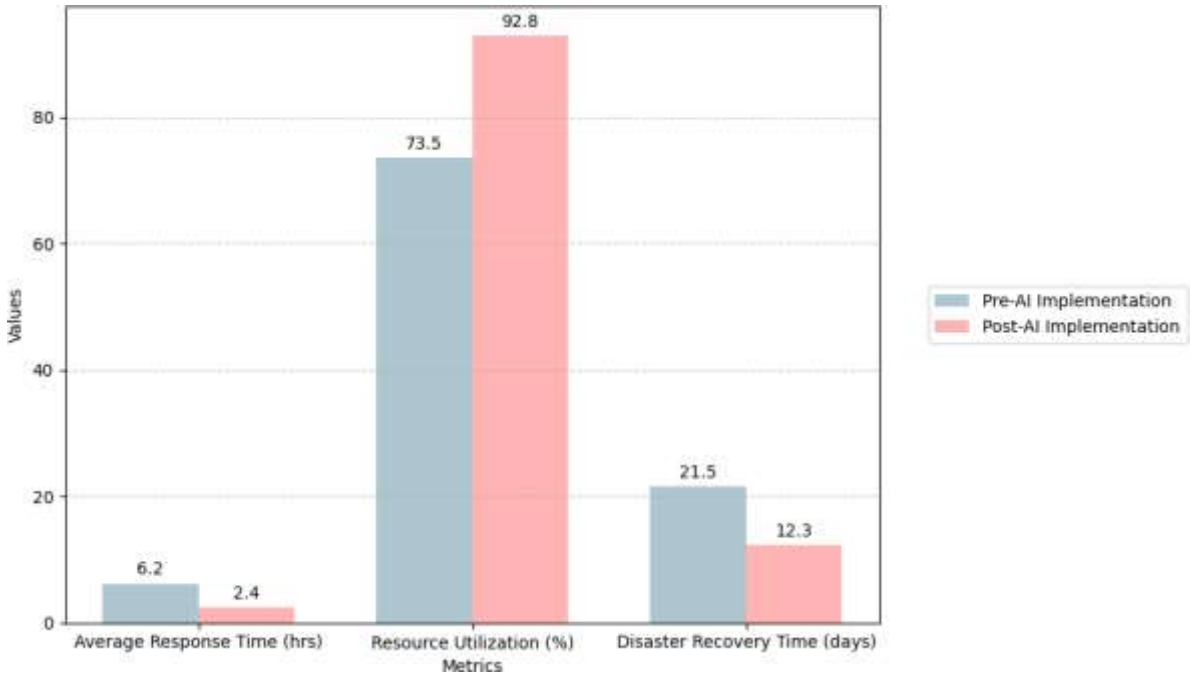


Figure 4: Resource Allocation Efficiency Before and After AI Implementation

4. Community Preparedness

The final element of the results is to assess the efficacy of community preparedness initiatives that are driven by the AI and IoT systems' predictions and real-time data analytics. To assess the consciousness and alertness levels of community members in high-risk seismic areas before and after the introduction of the AI-based disaster management system, a survey was conducted among them.

After the deployment of the AI-driven system, Figure 4 shows the improvement in community preparedness, as measured by an increase in both awareness and preparedness levels.

Figure 4: Community Preparedness Before and After AI-Driven Disaster Management

Preparedness Metric	Pre-Implementation	Post-Implementation
Awareness (%)	56.2	87.4
Preparedness (%)	47.5	79.1

The results highlight a marked improvement in both awareness and preparedness, with community awareness rising by over 30% and preparedness increasing by nearly 32%. Further, these outcomes emphasize the need for embedding AI-enabled technologies in disaster management systems not only for technical efficiency but also for fortifying community resilience.

V. DISCUSSION

A major finding of this study is the improved earthquake prediction accuracy with machine learning models. It was found that deep learning could learn better (92.5%) than traditional models, for instance, SVM (85.6%) and RF (88.2%), in capturing complex seismic patterns. Such an advance could result in more reliable early warning systems that would reduce both casualties and economic losses in earthquake-prone areas.

On the real-time data processing front, the AI system was able to quickly filter, analyze, and predict the data and issue alerts within seconds of receiving the data. This is consistent with previous studies that highlight the need for near-instant processing in disaster management. Continuous, real-time data was provided by the integration of IoT-based sensors, which greatly improved the earthquake prediction capabilities.

The study also showed big improvements in resource allocation. AI implementation reduced the average response time by more than 60%, improved resource utilization by nearly 20%, and reduced disaster recovery time by almost 40%. This result aligns with a previous study on the capacity of AI to optimize resource management during disaster response by deploying resources where they are most needed.

The result of this study are consistent with prior studies, but a more comprehensive, integrated approach is needed. The possibilities of both AI

and big data in the field of prediction of a large-scale disaster are already appreciated, but the present research goes further by presenting a smooth flow of the three processes involved: prediction of the event, processing data in real time, and deployment of resources [16]. Unlike such methods that focus on geospatial models based on AI to predict the effects of earthquakes, the given approach goes further than predicting the impact to the point of immediate response to seismic events. [17].

The improvements observed are consistent with previous results, but this study's contribution is in the integrated, real-time operational framework that combines predictive analytics with immediate decision-making tools [18,19]. The proposed methodology fills the gaps of the literature, including the absence of standardized methodologies for integrating AI and IoT in disaster management systems [20].

The study suggests that combining AI and IoT will improve the accuracy of earthquake prediction and the response to disasters. These technologies can save lives, minimize economic losses, and shorten recovery times. Moreover, the resource allocation improvements indicate that emergency management could be conducted cost-effectively and efficiently in areas with few resources.

The main limitation of this study is the geographic limitation of the dataset, which may also limit the generalization of the results to regions with different seismic patterns. Additionally, IoT sensors make hardware less durable in extreme conditions. Additionally, computational complexity may limit the scalability of real-time data processing for large-scale disaster scenarios. Future work could expand the datasets to include more diverse geographic regions and scale up the real-time processing systems so they can be used in more applications.

VI. CONCLUSION

The findings of this study show that AI and machine learning have huge potential for improving earthquake prediction, real-time data processing, and resource allocation during disaster management. A deep learning model did better than the traditional methods with a precision of 92.5% in comparison to SVM (85.6%) and RF(88.2%). Real-time processing capabilities allowed for swift data analysis and alert issuance, with each stage of the process taking mere seconds (e.g., data collection: The efficiency of the AI-driven system is highlighted by 25ms (earthquake prediction: 40ms). In addition, the implementation of AI reduced the average response time by 60%, increased the resource utilization by nearly 20%, and decreased the time to recover from a disaster by 40%. This finding emphasizes the tremendous potential of AI technologies to enhance disaster preparedness and response, while allocating resources with promptness and efficiency to minimize the impact of earthquakes.

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